## Dynamic Programming

We'd like to have "generic" algorithmic paradigms for solving problems

Example: Divide and conquer

- Break problem into independent subproblems
- Recursively solve subproblems (subproblems are smaller instances of main problem)
- Combine solutions


## Examples:

- Mergesort,
- Quicksort,
- Strassen's algorithm
- ...

Dynamic Programming: Appropriate when you have recursive subproblems that are not independent

## Example: Making Change

Problem: A country has coins with denominations

$$
1=d_{1}<d_{2}<\cdots<d_{k}
$$

You want to make change for $n$ cents, using the smallest number of coins.
Example: U.S. coins

$$
d_{1}=1 \quad d_{2}=5 \quad d_{3}=10 \quad d_{4}=25
$$

Change for 37 cents - 1 quarter, 1 dime, 2 pennies.
What is the algorithm?

## Change in another system

Suppose

$$
d_{1}=1 \quad d_{2}=4 \quad d_{3}=5 \quad d_{4}=10
$$

- Change for 7 cents - 5,1,1
- Change for 8 cents - 4,4

What can we do?

## Change in another system

Suppose

$$
d_{1}=1 \quad d_{2}=4 \quad d_{3}=5 \quad d_{4}=10
$$

- Change for 7 cents - 5,1,1
- Change for 8 cents - 4,4

What can we do?

The answer is counterintuitive. To make change for $n$ cents, we are going to figure out how to make change for every value $x<n$ first. We then build up the solution out of the solution for smaller values.

## Solution

We will only concentrate on computing the number of coins. We will later recreate the solution.

- Let $C[p]$ be the minimum number of coins needed to make change for $p$ cents.
- Let $x$ be the value of the first coin used in the optimal solution.
- Then $C[p]=1+C[p-x]$.

Problem: We don't know x.

## Solution

We will only concentrate on computing the number of coins. We will later recreate the solution.

- Let $C[p]$ be the minimum number of coins needed to make change for $p$ cents.
- Let $x$ be the value of the first coin used in the optimal solution.
- Then $C[p]=1+C[p-x]$.

Problem: We don't know x.

Answer: We will try all possible x and take the minimum.

$$
C[p]=\left\{\begin{aligned}
\min _{i: d_{i} \leq p}\left\{C\left[p-d_{i}\right]+1\right\} & \text { if } p>0 \\
0 & \text { if } p=0
\end{aligned}\right.
$$

## Example: penny, nickel, dime

$$
C[p]=\left\{\begin{aligned}
\min _{i: d_{i} \leq p}\left\{C\left[p-d_{i}\right]+1\right\} & \text { if } p>0 \\
0 & \text { if } p=0
\end{aligned}\right.
$$

```
Change (p)
if \((p<0)\)
    then return \(\infty\)
elseif \((p=0)\)
    then return 0
    else
return \(1+\min \{\operatorname{Change}(p-1), \operatorname{Change}(p-5), \operatorname{Change}(p-10)\}\)
```

What is the running time? (don't do analysis here)

## Dynamic Programming Algorithm

```
DP-Change (n)
\(C[<0]=\infty\)
\(C[0]=0\)
for \(p=1\) to \(n\)
    do \(\min =\infty\)
    for \(i=1\) to \(k\)
do if \(\left(p \geq d_{i}\right)\)
then if \(\left.\left(C\left[p-d_{i}\right]\right)+1<\min \right)\)
then \(\min =C\left[p-d_{i}\right]+1\)
coin \(=i\)
10
11
    \(C[p]=\min\)
\(12 \quad S[p]=\) coin
```

Running Time: $O(n k)$

## Dynamic Programming

## Used when:

- Optimal substructure - the optimal solution to your problem is composed of optimal solutions to subproblems (each of which is a smaller instance of the original problem)
- Overlapping subproblems


## Methodology

- Characterize structure of optimal solution
- Recursively define value of optimal solution
- Compute in a bottom-up manner


## Example: Rod Cutting

Problem: Given a rod of length $n$ inches and a table of prices $p_{i}$ for $i=1,2, \ldots, n$, determine the maximum revenue $r_{n}$ obtainable by cutting up the rod and selling the pieces.

| length $i$ | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 |
| :--- | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| price $p_{i}$ | 1 | 5 | 8 | 9 | 10 | 17 | 17 | 20 | 24 | 30 |

How can we cut a rod of length 4 ?

## Optimal Substructure

Suppose that we know that optimal solution makes the first cut to be length $k$, then the optimal solution consists of an optimal solution to the remaining piece of length $n-k$, plus the first piece of length $k$

Suppose not. Then we are saying that the optimal solution consists of some way to cut the piece of length $n-k$ that is not optimal, plus the piece of length $k$. Let $p_{k}$ be the profit from the piece of length $k$, and let $y$ be profit from the non-optimal solution to the piece of length $n-k$. Then we are receiving a total profit of $y+p_{k}$. Now suppose that instead of the proposed solution to the piece of length $k$, we used an optimal solution to the piece of length $k$ instead. Let $y^{\prime}$ be the profit associated with the optimal solution to the piece of length $n-k$, and since it is optimal $y^{\prime}>y$. We could then put this together with the piece of length $k$ and obtain a solution of profit $y^{\prime}+k>y+k$, contradicting the claim that the original solution was optimal.

## Recursive Implementation

Recurrence

$$
\begin{equation*}
r_{n}=\max _{1 \leq i \leq n}\left(p_{i}+r_{n-i}\right) \tag{1}
\end{equation*}
$$

Code

```
Cut \(-\operatorname{Rod}(p, n)\)
1 if \(n==0\)
2 then return 0
\(3 \quad q \leftarrow-\infty\)
4 for \(i \leftarrow 1\) to \(n\)
\(5 \quad\) do \(q \leftarrow \max (q, p[i]+\operatorname{Cut}-\operatorname{Rod}(p, n-i))\)
6 return \(q\)
```

What is the running time?

## DP solution

```
Bottom - Up - Cut \(-\operatorname{Rod}(p, n)\)
1 let \(r[0 \ldots n]\) be a new array
\(2 r[0] \leftarrow 0\)
3 for \(j \leftarrow 1\) to \(n\)
\(4 \quad\) do \(q \leftarrow-\infty\)
\(5 \quad\) for \(i \leftarrow 1\) to \(j\)
\(6 \quad\) do \(q \leftarrow \max (q, p[i]+r[j-i])\)
\(7 \quad r[j] \leftarrow q\)
8 return \(r[n]\)
```

What is the running time?

